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Evapotranspiration Modelling using Artificial Neural Network and Multiple Linear Regression Approach in Semi-Humid Region of Sikkim

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Abstract

This study investigates superiority between multiple linear regression (MLR) and artificial neural network (ANN) approach for prediction of weekly reference evapotranspiration (ET_0) in semi-humid region of Sikkim, India. Daily meteorological parameters (1985–2009) were used for the estimation of ET_0 using Penman Monteith equation and various combinations of meteorological parameters was used for MLR and ANN model development. Predicted ET_0 were compared with ET_0 estimated using coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), mean absolute relative error (MARE) and Nash Sutcliffe efficiency (NSE). Among ANN models, ANN model 4 with one hidden layer and four neurons had smallest RMSE (0.62 & 0.49 mm/day) and highest R^2 (0.75 & 0.82) for training and testing phase. ANN model 4 had highest NSE compared to MLR model 4. Comparison between MLR and ANN models revealed more accuracy of ANN to predict weekly ET_0 for the sub humid region like Tadong in East Sikkim district of North-eastern India. Study show the effectiveness of the both MLR and ANN models for estimation of the ET_0 with minimal meteorological variables and increased parameters increases the model prediction efficiency. The findings of the study could be helpful for similar studies in the data scarce northeast Indian part and other identical climatic regions.

1. Introduction

Evapotranspiration is a key component of hydrological cycle and play a vital role in our environment at global, regional, and local scales. Precise estimation of evapotranspiration is essential for the quantification of water budgeting, hydrological design of soil and water conservation structures, water resource planning and design of irrigation system (Patle & Singh, 2015; Phad et al. 2019). Evapotranspiration is a complex phenomenon and affected variation in the weather parameters and crop growth stages. Evapotranspiration process is unnoticeable and direct measurement are difficult therefore several models and methods have been developed to estimate the rate of evapotranspiration from meteorological data under different climatic conditions (Kumar, 2017). Reference evapotranspiration (ET_0) is usually estimated using physically based FAO Penman-Monteith Equation and which provide the best estimates of PET over various climatic types (Ahmad et al. 2017).

Estimation of ET_0 requires major climatic parameters and availability of these parameters are not always possible because of the remote location and weather condition and to overcome this deficiency, several empirical equations, requiring the less input weather parameters has been developed. But these empirical equations are developed for specific regions and climatic types therefore, it is possible that their estimates will be deemed by source of bias deriving from site-specific conditions. Data driven modelling approach such as multiple linear regression (MLR) and artificial neural networks (ANNs) are widely used for the prediction of hydro-meteorological parameters namely rainfall, temperature, wind speed relative humidity (Maqsood et al. 2004; Rajendra et.al. 2019), global solar radiations (Goddard et al. 2001), soil temperature (Rajendra et.al. 2019) Rainfall, runoff and sediment modelling (Chakravarti et al. 2015; Sharma et al, 2015), groundwater quality parameters and stream discharge (Nathan et al. 2017; Khan et al. 2016; Tiwari et al. 2016), Prediction of storms (Litta et al. 2013), including evapotranspiration (Sriram and Rashmi 2014). MLR is a statistical modelling technique and ANN is a robust machine learning (ML) technique. ANNs are computational models that can be used for the modelling of complex relationships by simulating the functional aspects of biological neural networks (Khedkar et al. 2019). ANNs and MLR techniques have been widely used for modelling of the potential ET process (Kumar et al. 2008; Zanetti et al. 2007; Chauhan and Shrivastava 2009; Chattopadhyay et al. 2009; Khedkar et al. 2008; Mallikarjuna and Kamasani, 2012). Kumar et al. 2002 developed an ANN model for the prediction of reference evapotranspiration (ET_0) and reported that the ANN model can predict ET_0 better than the conventional method. Jain et al. (2008) indicated that ANNs can efficiently estimate ET_0 from the limited meteorological variables of temperature and radiation only. They also reported that model prediction accuracy for the ET_0 estimation was less using the minimum parameters in the analysis and subsequently increased with adding more input parameters. Reddy et al. (2010) estimated weekly reference evapotranspiration using Linear Regression and ANN Models for different locations of Andhra Pradesh found satisfactory performance of MLR models in the weekly ET_0 estimation. Marti et al. (2010) described different approaches based on multiple linear regression, simple regression and artificial neural networks (ANNs) for reference evapotranspiration. They reported that the artificial neural network and the multiple linear regression approaches showed very similar performance accuracies, considerably higher than simple regression and traditional temperature-based approaches.

Dai et al. (2009) investigated the predictive ability of ANNs for the prediction of ET_0 in arid, semi-arid and sub-humid areas of Mongolia & China and reported that regional ET_0 can be satisfactorily estimated using ANN models. Mokarram and Sathyamoorthy (2015) compared the multiple regression and artificial neural network models for prediction of evapotranspiration in the southwest of the Fars province, Iran and observed superiority of ANN over the MLR technique. Ozgur and Vahdettin (2016) compared the six different multi-layer perception (MLP) algorithms for modelling of reference evapotranspiration (ET_0) with those of the multiple linear regression models and reported that that the Levenberg-Marquardt was faster and had a better accuracy than the other five training algorithms in modelling ET_0. Sriram and Rashmi (2014) used multiple linear regression method for the estimation of potential evapotranspiration. Vyas and Subbaiah (2016) found that the prediction of ANN was close to the ET_0 obtained by FAO Penman Monteith for Junagarh, Gujarat.

From the literature and review it is found that precise estimation of evapotranspiration is important for the quantification of hydrological water balance, hydrological design, water resource planning and management, irrigation system design and management, and crop yield simulation. ANNs and MLR techniques have been commonly used for modelling of the reference evapotranspiration. In hilly region of Sikkim, availability of all meteorological parameters is very difficult for the estimation of the reference evapotranspiration (ET_0). Therefore, an attempt has been made to identify the best prediction models of ET_0 using MLR and ANN approach.

2 Materials And Methods

2.1 Study area and data used

Study area comprises the east district of Sikkim in India and is situated in the eastern Himalayan range. Sikkim is a small state located in the unfathomable mountain and abrupt valleys. It is bounded approximately between 27º 05’ to 27º 09’ North Latitudes and 87º 59’ to 88º 56’ East Longitudes covering the total geographical area of 7096 km^2 (Fig. 1). The altitude in the state ranges from 280 m to 8,585 m above mean sea level. The climate of Sikkim state varies from sub-tropical to temperate. The average annual rainfall of east district of Sikkim is about 3067 mm. The minimum and maximum air temperature ranges from 13ºC to 28ºC and 0ºC to 13ºC in summer and winter months, respectively. Daily mean relative humidity varies from 64–85%. The highest and lowest wind speed of 3 and 1 kmph, with an annual average of 2 kmph. Daily meteorological data of 25-years (1985–2009) including maximum air temperature (T_{max}), minimum air temperature (T_{min}), maximum relative humidity (RH_{max}), minimum relative humidity (RH_{min}) and Solar Sunshine hours (SSH) were used in the study. Data was collected from the Indian Meteorological Department (IMD) observatory located at 27.3106 ºN latitude, 88.5976ºE longitude and an altitude of 1322 m above mean sea level.

Insert Fig. 1. **Here**

2.2 Estimation of reference evapotranspiration

The FAO Penmen-Monteith equation was used for estimation of reference evapotranspiration (ET_0) as proposed by Allen et al. (1998). The Eq. (1) is represented as given below

$$ET_o = \frac{0 \cdot 408\Delta\left(Rn - G\right) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma\left(1 + 0 \cdot 34u_2\right)}$$

1

Where, ET_0: reference evapotranspiration [mm day^{-1}], R_n: net radiation at the crop surface [MJ m^{-2} day^{-1}], G: soil heat flux density [MJ m^{-2} day^{-1}], T: mean daily air temperature at 2 m height [°C], u_2: wind speed at 2 m height [m s^{-1}], e_s: saturation vapour pressure [kPa], e_a: actual vapour pressure [kPa], (e_s - e_a): saturation vapour pressure deficit [kPa], Δ: slope vapour pressure curve [kPa $°C^{-1}$], and γ: psychrometric constant [kPa $°C^{-1}$]. All the variables in Eq. (1) were calculated using the standard procedure outlined by Allen et al. (1998). P can be calculated by following equation:

$$P = 101.3\left(\frac{293 - 0.0065z}{293}^{5.26}\right)$$

2

Where, z is elevation above sea level (m).

$$e_s = \frac{e^0\left(T_{max}\right) + e^0\left(T_{min}\right)}{2}$$

3

$$e^0\left(T\right) = 0.6108\left[\frac{17.27T}{T + 237.3}\right]$$

4

$$\Delta = \frac{4098\left[0.6108_{exp}\left(\frac{17.27T}{T+237.3}\right)\right]}{\left(T + 237.3\right)^2}$$

5

Where, Δ is the slope of saturation vapor pressure curve at air temperature T, T: air temperature (∘C); The slope of the vapor pressure curve is calculated using mean air temperature (∘C).

$$e_a = \frac{e^0\left(T_{min}\right)\left(RH_{max}/100\right) + e^0\left(T_{max}\right)\left(RH_{max}/100\right)}{2}$$

6

$$R_n = R_{ns} - R_{n1}$$

7

$$R_{ns} = \left(1 - \alpha\right).R_s, \alpha = 0.23$$

8

$$R_s = \left(0.25 + 0.50\frac{n}{N}\right)R_a$$

9

Where, '*n*' is actual duration of sunshine hours. The values of *N* and *R*a can be obtained from standard tables (Allen et. al., 1998) for different latitudes and months.

The weekly average reference evapotranspiration values were estimated from the estimated daily ET_0. Average wind speed of 2 kmph was used for the estimation of ET_0.

2.3 model development

The Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) method was used for the development of prediction models for ET_0 in the present study. The performance of the models was verified through selected performance evaluation criteria. Linear Regression represents the relationship between variables in which the unknown parameters of the regression model are estimated using the data instances. Multilinear regression (MLR) is a statistical model that contains more than one predictor variable. The general form of the first order MLR model is shown in Eq. 10.

$$ET_0 = C + a_1 X_1 + a_2 X_2 + \ldots\ldots + a_n X_n + \varepsilon \quad (10)$$

Where, a_1, a_2…… and C are empirical constants and X_1, X_2, ….are the meteorological parameters and ε is the random error term with assumed normal distribution. All data subsets employed in the statistical analysis were exactly the same as those used with ANN and the best equation was selected based on the error statistics associated with the cross-validation dataset.

2.3.1 Artificial neural network model (ANN)

Artificial Neural Network (ANN) was first introduced as a mathematical aid (McCulloch *et al.*1943). The main processor of artificial intelligence based-models is Neuron. They are arranged in groups called layers. The basic structure of a network usually consists of three layers viz., input layer, hidden layer and output layer. The basic structure of an ANN model used in this study is shown in Fig. 2.

Insert Fig. 2. **Here**

There are many types of neural networks for various applications available in the literature. The multilayer perceptron (MLP) is a widely used ANN configuration and has been frequently applied in the field of hydrological modelling (Leahy et al. 2008). The MLP is the simplest and therefore, most commonly used neural network architectures. Multi-layer perception (MLP) neural networks that consist of three types of layers namely the input layer, one or more hidden layers and output layer using sigmoid transfer functions. An arbitrary number of hidden layers placed in between the input and output layer are the true computational engine of the multi-layer perception. The MLPN transform n inputs to m outputs through some nonlinear function. Architecture of the network (the number of hidden layers and neurons in hidden layers) were determined by trial and error (Hagan and Menhaj 1994). In this study, a back propagation (BP) algorithm was employed to train our MLP neural network. Levenberg–Marquardt (LM), a second-order nonlinear optimization technique was chosen from the various BP training algorithms available for use in this study.

2.3.2 Input combinations of climatic parameters for model development

In this study, the various combinations of the meteorological parameters as inputs to MLR and ANN models were used to evaluate the degree of effectiveness on reference evapotranspiration (ET_0) and are shown in Table 1. Meteorological parameters were considered in the incremental approach and given as input to the MLR and ANN models. Daily climate parameters namely air temperature (Minimum and maximum), Relative humidity (minimum and maximum), wind speed and sunshine hour was collected from the India Metrological Department observatory located at Tadong, East Sikkim and was used in this study.

Table 1
The various input combinations of the meteorological parameters.

Model	Combination of input parameter
1	T_{max} and T_{min}
2	$T_{max,}$ T_{min} and Rh_{max}
3	$T_{max,}$ $T_{min,}$ Rh_{max} and Rh_{min}
4	$T_{max,}$ $T_{min,}$ $Rh_{max,}$ Rh_{min} and SSH

Insert Table 1. **Here**

The meteorological data set was divided in the proportion of 70:30 ratios for both the MLR and ANN modelling. The data were divided into two phases as training and testing phase, respectively. The 70% of the data was taken in the training phase i.e. (1985–2002) and the remaining 30% of the data was taken in the testing phase i.e. (2003–2009). ET_0 estimated by the FAO Penman Monteith equation was used as output to the multiple linear regression and artificial neural network model. The number of hidden nodes in the artificial neural network is determined empirically by trial and error, considering the need to derive reasonable results. The inputs and outputs of the data sets were normalized to improve the performance of the network. The process was carried out using SPSS Software.

2.4. Performance evaluation criteria

The performances of the models developed in this study were evaluated using statistical criteria namely coefficient of determination (R^2), root mean square error (RMSE), Nash Sutcliffe efficiency (NSE), mean absolute error (MAE) and mean absolute relative error (MARE), (Khoob 2008). Following equations (11, 12, 13, 14 and 15) were used for the judgement of the models

$$R \ = \frac{\sum_{i=1}^{n}(Xi - Xi')(Yi - Yi')}{\sqrt{\sum_{i=1}^{n}(Xi - Xi^{'})\ (Yi - Yi^{'})}}$$

11

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Xi - Yi)}{n}}\ (12)$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(Yi - Xi)}{\sum_{i=1}^{n}(Yi - Xi^{'})}\,(13)$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|Xi - Yi|}{n}\,(14)$$

$$\mathrm{MARE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|Xi - Yi|}{Xi} * 100\,(15)$$

Where, Xi and Yi are the i^{th} observed values and i^{th} predicted values, respectively. Xi' and Yi' are the mean of Xi and mean of Yi and n is the total number of data.

3. Result And Discussion

3.1. Variation in weekly reference evapotranspiration (ET_0)

Variation in the average weekly ET_0 over the period 1985–2009 is shown in Fig. 3. It was observed that the minimum and maximum ET_0 was 3.33 mm day^{-1} and 6.96 mm day^{-1} in the week number 52 and 20, respectively in the study area.

Insert Fig. 3 **here**

The models were developed using various combination of meteorological parameters as shown in Table 1. Model equations for both training and testing phases using MLR analysis was developed. Prediction equations for the estimation of ET_0 for training and testing dataset are shown in Table 2. Coefficients against the input variables (meteorological parameters) are shown in the equations. The predicted ET_0 from various developed models were compared with the ET_0 estimated from FAO Penman Monteith model using statistical indices including coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), mean absolute relative error (MARE) and Nash Sutcliffe efficiency (NSE).

Table 2
Predicted equations for training and testing of MLR models

MLR Models	Prediction equations
MLR model 1 (Training)	Predicted ET_0 = -1.03 + 033(Tmax,°C)-0.12(Tmin,°C)
MLR model 1 (Testing)	Predicted ET_0 = -2.46 + 0.45(Tmax,°C)-0.22(Tmin, °C)
MLR model 2 (Training)	Predicted ET_0 = 1.85 + 0.33(Tmax, °C)-0.07(Tmin, °C)- 0.03 (RHmax, %)
MLR model 2 (Testing)	Predicted ET_0 = -5.20 + 0.48(Tmax, °C)-0.25(Tmin, °C) + 0.03 (RHmax,%)
MLR model 3 (Training)	Predicted ET_0 = 5.33 + 0.15(Tmax,°C) + 0.12(Tmin,°C)-0.03(RHmax,%) -0.04(RHm%)
MLR model 3 (Testing)	PredictedET_0=-5.07 + 0.46(Tmax,°C)-0.22(Tmin,°C) + 0.03(RHmax,%) -0.01(RHm%)
MLR model 4 (Training)	Predicted ET_0 = 4.09 + 0.11(Tmax,°C) + 0.15(Tmin,°C)-0.03(RHmax,%) -0.03(RHmin,%) + 0.14(SSH)
MLR model 4 (Testing)	Predicted ET_0 = 3.18 + 0.34(Tmax,°C)0.12(Tmin,°C) + 0.02(RHmax,%) + 0.002(RHmin,%) + 0.17(SSH)

From comparison of observed and predicted $ET_{0,}$ it was observed that the predictability of the model increased as increase in number of independent variable in the MLR model. It was also observed that the model 4 with the combination of climatic parameters namely T_{max}, T_{min}, RH_{max}, RH_{min} and SSH predicted better ET_0 as compared to other models and it is depicted by the highest R^2 and minimum RMSE value for training and testing phase, respectively. The statistical performance evaluation criteria of MLR are presented in Table 3. The MLR model whose inputs are T_{max}, T_{min}, RH_{max}, RH_{min}, SSH and WS had the smallest RMSE (0.67 & 0.49 mm day^{-1}), MAE (0.54 & 0.40 mm day^{-1}), MARE (10.86 & 8.47) and the highest R^2 (0.71 & 0.82) for training and testing phases, respectively. The goodness of fit among the observed and predicted ET_0 for training and testing for MLR model 4 is shown in Fig. 4.

Table 3
The statistical performance criteria of multiple linear regressions (MLR).

Performance Criteria	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	T,t	**T,t,Rh**	**T,t,Rh, Rh**	**T,t,Rh,rh,S**
Training Phase				
R^2	0.58	0.60	0.67	0.71
MAE (mm/day)	0.61	0.60	0.57	0.54
MSE $(mm/day)^2$	0.64	0.62	0.50	0.45
RMSE(mm/day)	0.80	0.79	0.71	0.67
MARE %	12.05	11.92	11.33	10.86
NSE	0.28	0.33	0.51	0.58
Testing Phase				
R^2	0.79	0.80	0.81	0.82
MAE (mm/day)	0.43	0.42	0.42	0.40
MSE $(mm/day)^2$	0.28	0.27	0.27	0.24
RMSE(mm/day)	0.53	0.52	0.52	0.49
MARE %	8.92	8.83	8.86	8.47
NSE	0.74	0.75	0.76	0.79

The result was very satisfactory and indicates that the relationship between the two series found very high. Thus, predictability of MLR models has improved subsequently. In general, the results showed that the MLR can be an acceptable approach to predict weekly ET_0.

Insert Table 2. **Here**

Insert Table 3. **Here**

Insert Fig. 4: **Here**

ANN models were developed through the combination of meteorological parameters. Similar to MLR model development, in case of ANN the dataset was partitioned in the ratio 70:30 for training and testing of models. The training set was used to fit ANN model weights and the testing phase were used to evaluate the chosen model against unseen data. The R^2, RMSE, MAE and MARE statistics of each ANN model in testing and training phases are given in Table 4. The ANN model 4 whose inputs are T_{max}, T_{min}, RH_{max}, RH_{min} and SSH has the smallest RMSE (0.62& 0.49 $mmday^{-1}$), MAE (0.50 & 0.40 $mmday^{-1}$), MARE (9.79 & 8.36) and the highest R^2 (0.75 & 0.82) for training and testing phases, respectively. The goodness of fit among the Observed and predicted ET_0 for training and testing for ANN Model 4 is shown in the Fig. 5.

Table 4
The statistical performance criteria obtained by ANN approach

Performance Criteria	Model1	Model 2	Model 3	Model 4
	T,t	T,t,Rh	T,t,Rh,rh	T,t,Rh,rh,S
Training Phase				
R^2	0.70	0.70	0.75	0.752
MAE (mm/day)	0.55	0.54	0.49	0.50
MSE $(mm/day)^2$	0.46	0.46	0.38	0.38
RMSE (mm/day)	0.68	0.68	0.62	0.62
MARE %	10.80	10.79	9.65	9.79
NSE	0.57	0.58	0.69	0.68
Testing Phase				
R^2	0.78	0.80	0.81	0.82
MAE (mm/day)	0.43	0.41	0.43	0.40
MSE $(mm/day)^2$	0.29	0.26	0.28	0.24
RMSE(mm/day)	0.54	0.51	0.53	0.49
MARE %	8.87	8.46	9.05	8.36
NSE	0.72	0.76	0.78	0.80

This emphasizes the factors influencing predicted ET_0, since the model considered all the variables. The comparison of the predicted ET_0 predicted by Model 4 and observed values at training and testing phases showed good agreement with R^2 which are 0.75 and 0.82, respectively. It can be seen from Table 4 that it is appropriate to take into account the combined influence of all the meteorological parameters on ET_0.

Insert Table 4 **Here**

Insert Fig. 5. **Here**

In order to optimize the architectural parameters, several runs were performed with different architectural configurations. In this study, the networks were trained and tested for each combination. Training and testing of the networks were accomplished on SPSS software. Although several tests were carried out using one and two hidden layers, it was observed that a single hidden layer with four neurons was the best architecture and predicted closer values to the observed ET_0 values. The simulations showed that an increase in the hidden layer and the number of neurons in the hidden layer has brought nearly no significant improvement to the ET_0 estimates. For the best architecture, the activation function was set to a Sigmoid function as this proved by trial and error to be the best in depicting the nonlinearity of the model natural system. The results showed that an increase in iterations value has brought nearly no significant improvement to the prediction of ET_0. Study also showed that the superiority of ANN predicted ET_0 over the MLR approach. Our results are in consistent with the performance of artificial Neural Network (ANN) approach for the prediction of reference evapotranspiration (ET_0) as reported by Reddy et al. (2010); Mokarram and Sathyamoorthy (2015), Khedkar et al. (2019). From several research findings, ANN approach showed its effectiveness with improved predictive capacity over the linear regression method and stated that data driving techniques are suitable over the conventional estimation methods. Sikkim state of India is mountainous region and crops are cultivated organically on the sloppy land transformed into bench terraces. Climatic conditions are suitable for the cultivation of variety of horticultural crops in entire state. Due to the topographical constraints, the irrigation facility and water storage structures are minimal. Therefore, precise estimation of evapotranspiration is a paramount in the planning of water resources for crop production system in hilly semi humid region of Sikkim. Inspite of region receiving high rainfall, crops suffer from water stress due to drying of natural springs (which are main sources for irrigation). Therefore, estimation of weekly reference evapotranspiration would be very helpful for the accurate estimation of crop water requirement, for planning and designing irrigation systems and water resource management planning in the hilly state of Sikkim and developed models using MLR and ANN approach would be helpful for the prediction of evapotranspiration using available climatic parameters.

4 Conclusions

Accurate estimation of evapotranspiration is a critical input for irrigation planning and water resources management. In order to estimate weekly ET_0, multiple linear regression and artificial neural network technique was used in this study to identify the best suitable model for the study area. Results showed that MLR and ANN model 4 was highly suitable for the prediction of reference evapotranspiration (ET_0) and in both the cases the prediction accuracy of the developed models improved by increasing the input variables. In case of limited climatic parameters, data driven modelling techniques would help effectively than the conventional evapotranspiration estimation methods. It is also suggested that other neural network models should be compared for the estimation of evapotranspiration for the similar study area for better accuracy in prediction with limited climate parameters.

Declarations

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Author contribution All authors have contributed equally and have read it thoroughly and approve the manuscript.

Ethics approval The authors declare that all the accepted principles of ethical and professional conduct have been followed in this research work.

Consent to participate Not applicable

Consent for publication The authors give the publisher the permission to publish this work. If required, we will also provide the signed consent to publish this paper.

Conflict of interest There is no conflict of interest among the authors.

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Figures

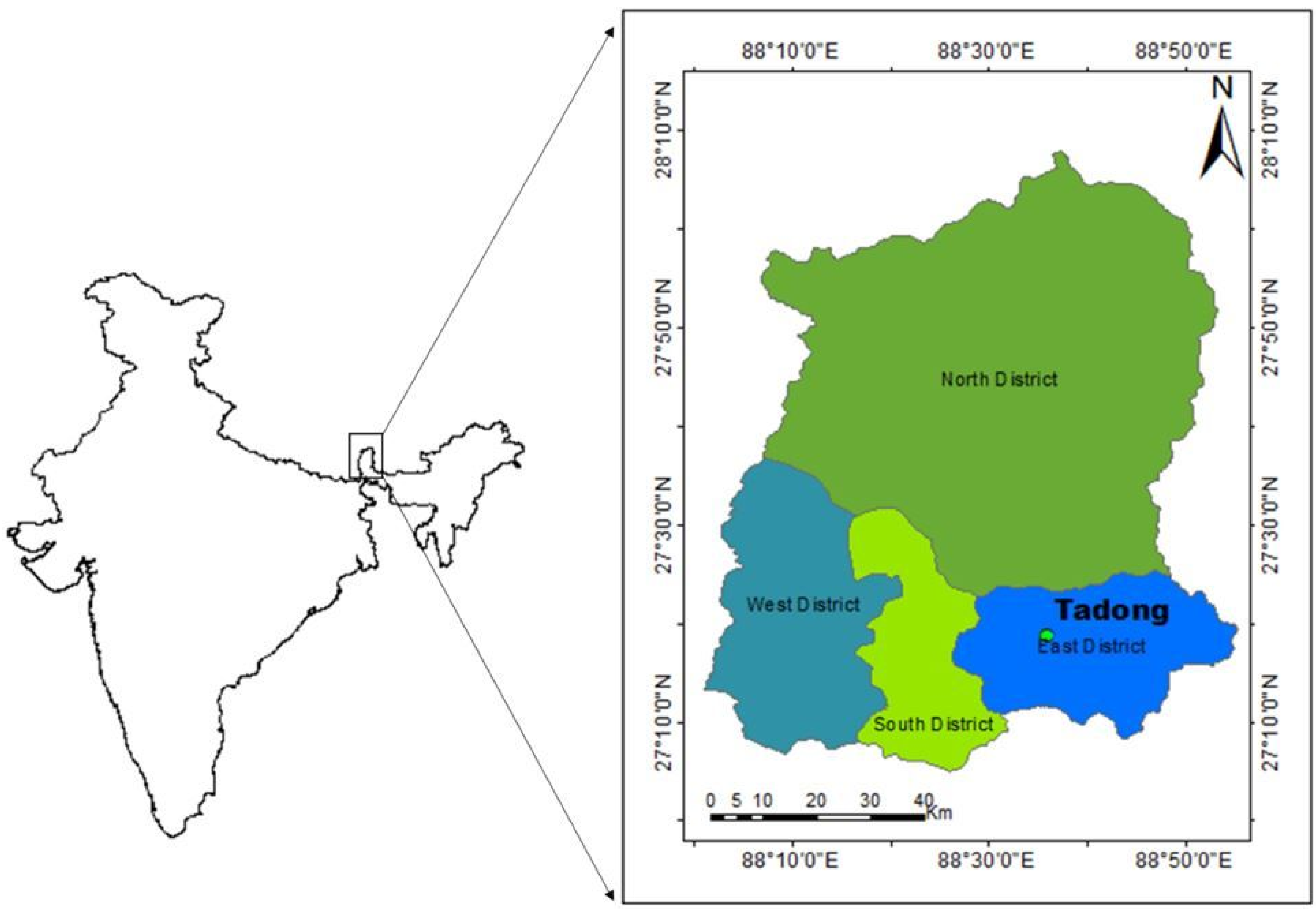

Figure 1

Geographic location of the study region and synoptic station

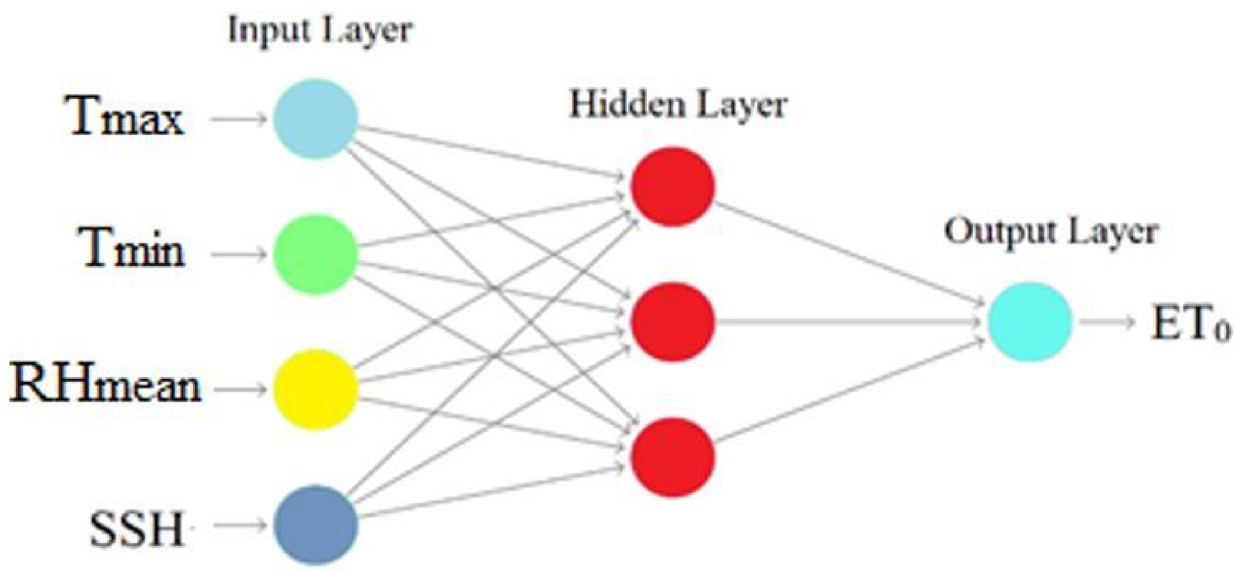

Figure 2

The basic structure of an ANN model used in this study

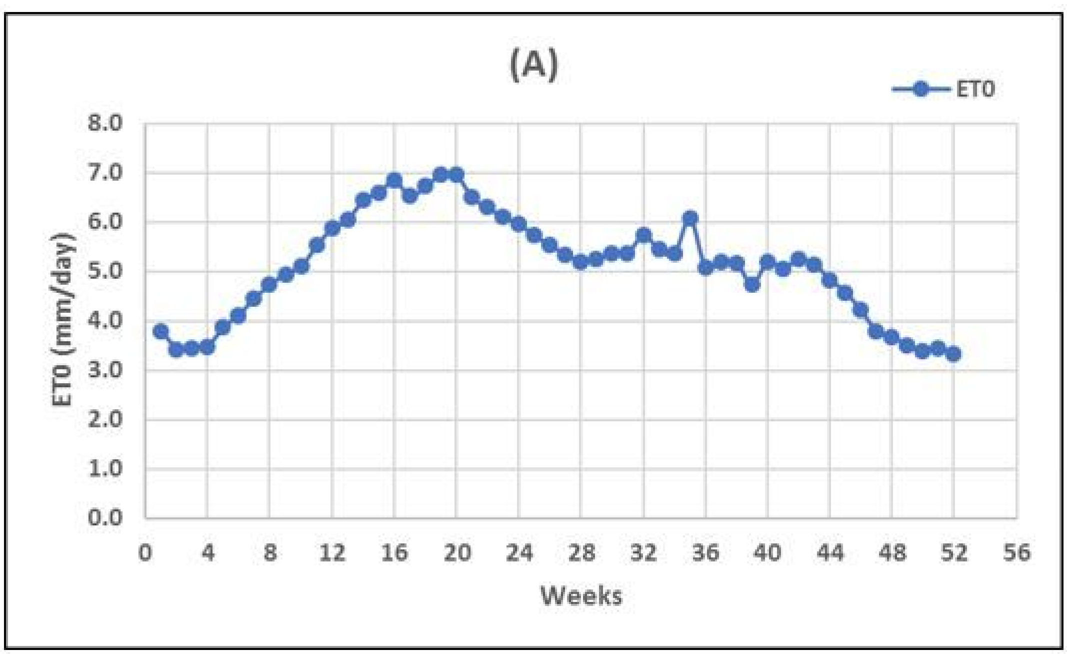

Figure 3

Variation in the average weekly ET_0 over the period 1985-2009

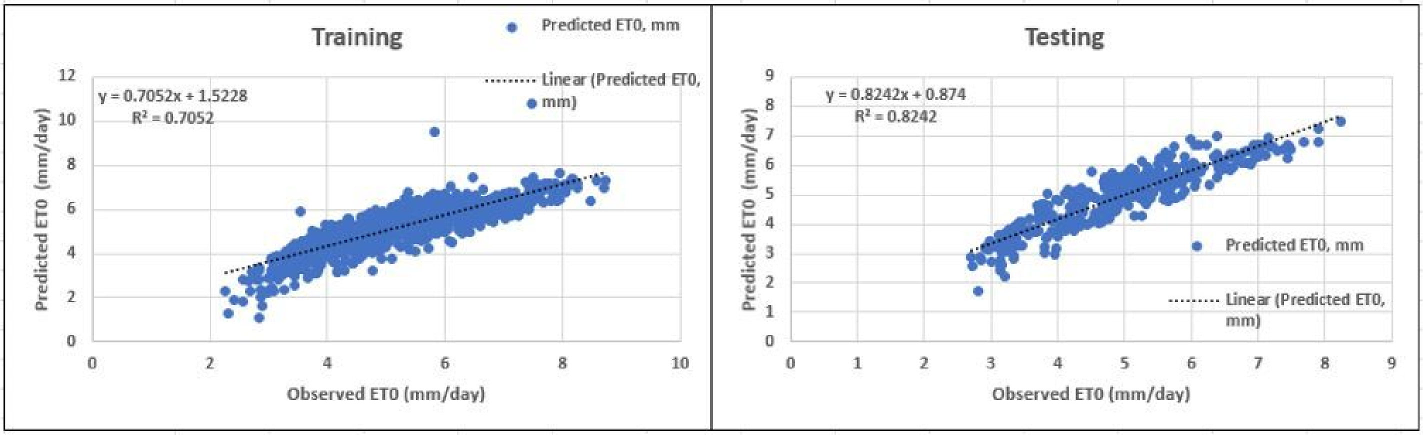

Figure 4

Observed and predicted ET_0 for training and testing for MLR Model 4

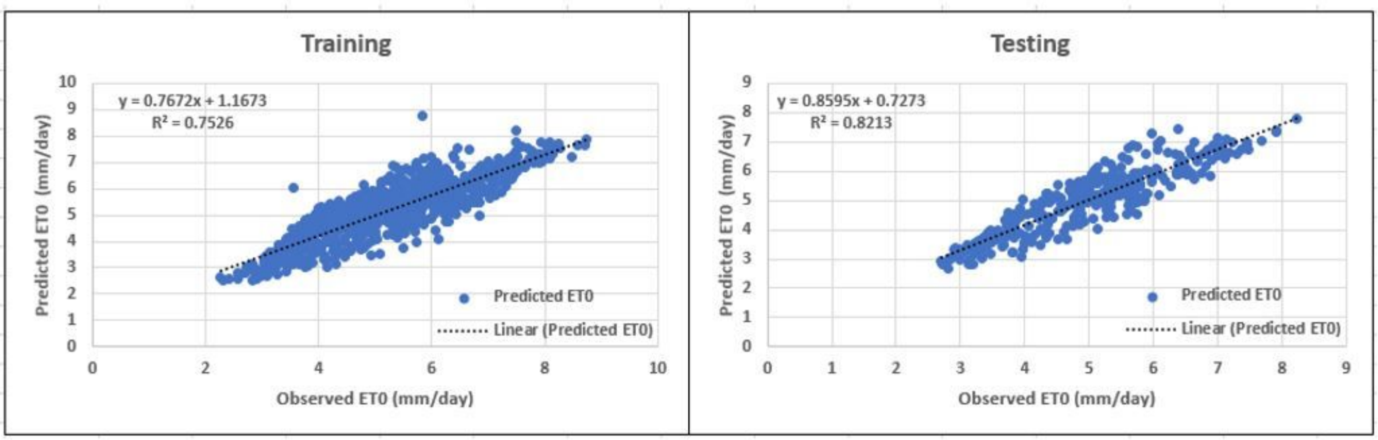

Figure 5

Observed and predicted ET_0 for training and testing for ANN Model 4